A Novel Framework for Optimizing Motor (Re)-learning with a Robotic Exoskeleton

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***Abstract*— A critical question to be answered to improve robotic rehabilitation is what is the optimal rehabilitation environment for a subject that will facilitate maximum recovery during therapy? Studies suggest that task variability, nature and degree of assistance or error-augmentation and type of feedback play a critical role in motor (re)-learning. In this work, we present a framework for robot-assisted motor (re)-learning that provides subject-specific training by allowing for simultaneous adaptation of task, assistance and feedback based on the performance of the subject on the task. We model a continuous and coordinated multi-joint task using a learning-from-demonstration approach, which allows the task to be modeled in a generative manner such that the challenge-level of the task could be modulated in an online manner. To train the subjects for dexterous manipulation, we present a torque-based task that requires the subject to dynamically regulate their joint torques. Finally, we carry out a pilot study with healthy human subjects using our previously developed hand exoskeleton to test a hypothesis and the results suggest that training under simultaneous adaptation of task, assistance and feedback positively affects motor learning.**

I. Introduction

Stroke often leads to a persistent impairment of the upper or lower limbs or both for a majority of the survivors [1]. Over 82% of the stroke survivors are left severely impaired as conventional therapies for stroke rehabilitation could only provide limited recovery. Robotic devices have been developed to aid in stroke rehabilitation, however, robotic therapy have so far shown similar outcomes [2]. This is because current robot-assisted therapy makes limited use of the general motor learning and neuro-rehabilitation principles, which have been experimentally verified over the years. An understanding of what type of task, robot control algorithm and feedback would result in maximum recovery could benefit robot-assisted rehabilitation.

Our idea is to first understand the key factors that affect motor learning and neuromuscular rehabilitation and then incorporate those in the robot control algorithm to give rise to a rehabilitation environment that is optimized for each subject and is adaptively tailored based on his or her performance and needs. Challenge point hypothesis and also related experiments suggest that optimal learning occurs when the challenge is matched with the skill level of the performer [3]. So far challenge in robotic rehabilitation has been modulated by only adjusting the amount of assistance provided by the robot during therapy. Experiments with this approach show that results are promising but there is limited success as just adjusting assistance may not be sufficient to affect true recovery. Task variability and augmented feedback have also been shown to affect motor learning and therefore can be used to modulate challenge [4], [5].

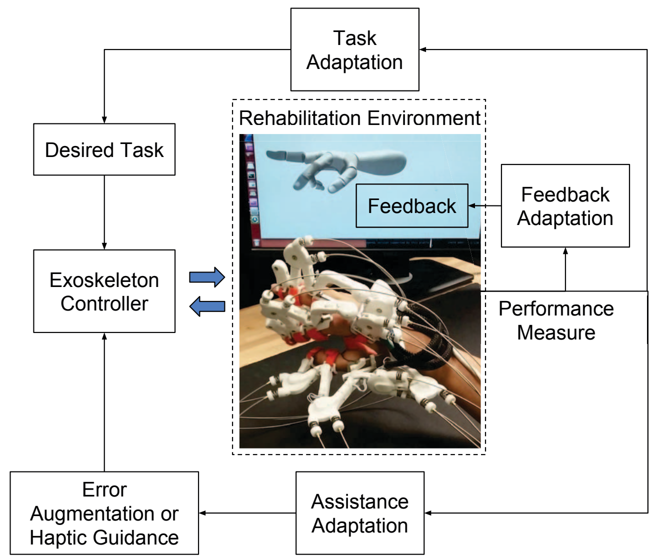

Fig. 1. An overview of the proposed framework for robot-assisted motor (re)-learning.

We present a framework for performance-based modulation of challenge in this multi-dimensional space (task, assistance and feedback) on motor learning and re-learning during rehabilitation (Fig. 1). The framework is designed around the idea of providing an optimum rehabilitation environment to each subject by adapting the environment variables to provide a challenge level commensurate with the level of the skill of the subject. The rehabilitation environment consists of a human subject performing a functional task with a robotic device, while the framework provides some form of feedback (e.g. verbal, visual, or auditory). The performance on the task is assessed using measures that estimate the level of skill of the subject. The framework consists of continuous adaptation along the following three dimensions based on the performance of the subject on a functional task: (i) task adaptation to introduce sufficient variability in the task for keeping the task optimally challenging based on the skill level of the subject, (ii) assistance adaptation to provide a haptic guidance or an error augmentation training while smoothly transiting between the two based on the subject's skill level, and (iii) feedback adaptation to provide just the

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right amount of feedback to avoid reliance on feedback and instead encourage motor adaptation and learning.

Our work makes the following novel contributions: (i) a framework for robot-assisted motor (re)-learning that provides subject-specific training by allowing for simultaneous adaptation of task, assistance and feedback based on the performance of the subject on the task, (ii) a learning-from-demonstration approach to model a continuous and coordinated multi-joint task in a generative manner such that the challenge-level of the task could be modulated in an online manner and (iii) a torque-based task that requires subject to dynamically regulate their joint torques capturing the essence of dexterous manipulation. The rest of the paper is organized as follows. We first review the limitations of the existing control strategies for rehabilitation (Section II), understand the factors that affect motor learning and neuromuscular rehabilitation (Section III) and the need for a torque-based task (Section IV). Next, we present our framework for robot-assisted motor (re)-learning and the three types of adaptation laws implemented for our experiments (Section V). Finally, a pilot study is carried out with human subjects using our hand exoskeleton to assess the effectiveness of training using the developed framework (Section VI) and the results of the study are presented (Section VII) and discussed (Section VIII).

II. Limitations of Existing Control Strategies for Rehabilitation

Several robot control strategies have been developed for rehabilitation of both the upper and the lower limbs, including assistive, challenge-based, haptic simulation and coaching [6]. A majority of the work has been done on implementing assistive strategies, including impedance-, force-field- and EMG-based controllers. Some adaptive control techniques (e.g. adaptive assist-as-needed) have also been developed that provide subject-specific assistance by modifying the control parameters [7], [8]. However, clinical studies carried out on stroke subjects using these control strategies have shown only very limited to no improvement over conventional therapy [2]. We believe that one of the reasons for the limited effectiveness of the existing control strategies is that so far these are primarily focused on only one of the aspects of what constitutes a rehabilitation environment, i.e., assistance. We first understand all the important factors that affect motor learning and neuromuscular rehabilitation and incorporate those in the robot control algorithm to give rise to an optimum rehabilitation environment that is subject-specific and is adaptively tailored based on his or her performance and needs. Next, we review the factors that have been shown to affect motor learning and neuromuscular rehabilitation.

III. Factors Affecting Motor Learning and Neuromuscular Rehabilitation

There are several factors that have been shown to affect motor learning and neuromuscular rehabilitation. In this work, our focus is on a few important ones that could be quantified. Practice variability hypothesis states that motor learning is better when a skill is performed in a variety of ways or contexts rather than one way [4], [9], [10], [11], [12], [13]. Even though practice variability produces more error during practice and learning, several studies have shown that introducing task variability in the acquisition session improves performance in subsequent sessions [14], [15]. This is because a constant task becomes monotonous and discourages motor learning by leading to memorization of the time sequence of muscle forces rather than actual learning of the skill. Also, some studies have shown that task-related functional training leads to long-lasting and better outcomes [16], [17], [18], [19].

Another important factor that influences motor learning is error augmentation or haptic guidance. Guidance refers to a variety of techniques including assisting the learner by providing appropriate amounts of forces or torques or preventing incorrect movements by means of physical limitations on the apparatus [20]. Error augmentation, on the other hand, refers to artificially increasing movement error during practice. It has been shown in the literature that many forms of learning, including motor learning, are processes that are error-driven [21], [22]. Milot et al. carried out a comparison study to understand whether error augmentation or haptic guidance leads to better motor learning for a timing-based task with healthy subjects [23]. Their study showed that error augmentation training was more beneficial for the skilled subjects whereas haptic guidance training was more effective for the less skilled subjects. Patton et al. also carried out a study to understand how motor adaptation takes place when the planar multi-joint movements of chronic stroke subjects are disturbed by a force-field [24]. Their study demonstrated that for individuals with stroke, enhancement of error in trajectory tracking using force fields improves learning as opposed to reduction of error or no assistance using force field. This shows that there is a need to develop robot control algorithms that provide the right type of training based on the skill level of the subject for the task at hand and adapt as the skill level of the subject changes. This conclusion is also in line with the challenge point hypothesis, which speculates that when optimal challenge is offered to the individuals based on their skill level, greater learning is achieved [3].

Augmented feedback has also been shown to play a significant role in motor learning in several studies [5], [25], [26], [27]. This type of feedback can be provided in the form of knowledge of results (outcome), knowledge of performance (e.g. quality or type of movement) or visual information (e.g. current and desired trajectory) about performance on the task. Some studies have shown that uncertainty in visual feedback determines the speed of motor adaptation and that noisy visual feedback reduces the rate of adaptation [28], [29]. Furthermore, guidance hypothesis predicts that augmented feedback is beneficial for motor learning when used to reduce error, but detrimental when relied upon [30]. A heavily guiding form of feedback might be detrimental for learning. Also, practice with a high relative frequency of augmented feedback would be detrimental for learning. Thus, there is a need to provide augmented feedback that adapts based on the subject-specific performance on the task and becomes easy or difficult to interpret to encourage motor learning [31].

IV. Need for a Torque-based Task

Force-control based strategies (e.g. impedance, admittance, assist-as-needed [32]) can be more effective for rehabilitation of both the upper [33], [34], [35] and lower limbs [6] than pure position-based control [36]. However, even though force-controlled devices have been developed for both the upper and lower limbs, these devices have so far focused on training for accuracy of movement and correlating position tracking accuracy with degree of rehabilitation [7], [37]. Studies have shown that the ability to dynamically control fingertip force is critical for dexterous manipulation [38], [39], [40]. Since manipulation heavily relies on applying appropriate interaction forces on the concerned object, a training paradigm that deals with training for forces or torques could be more effective in improving the manipulation skill. There exists a few studies where the subjects deal with an isometric manipulation task [41], [42], [43]. However, a training paradigm that provides subjects an opportunity to dynamically regulate finger joint torque or force could be more effective in developing the skill for dexterous manipulation. Thus, training to achieve desired torques at finger joints and assessing performance based on accuracy of torque tracking could be more effective to develop and assess manipulation skill.

V. Framework for Robot-assisted Motor (Re)-learning

We present a novel rehabilitation framework that combines aforementioned factors to provide an optimum rehabilitation environment with a challenge level commensurate with the level of the skill of the subject. This framework consists of a rehabilitation environment with a robotic device using which a task is performed by the subject, while the framework provides some form of feedback (Fig. 1). The performance on the task is measured using performance measures, which determine the level of skill of the subject. These performance measures are then used to carry out three forms of adaption. The role of adaptation at the task level is to introduce sufficient variability in the task to keep the task challenging based on the skill level of the subject. Adaptation in assistance is carried out to smoothly transition from a haptic guidance training to an error augmentation training based on the performance on the task. Finally, adaptation in feedback is carried out to provide just the right amount of feedback to avoid reliance on feedback and instead promote motor adaptation and learning. Different types of adaptation algorithms can be incorporated in this framework for each component. We implement the following three types of adaptations for our experiments.

A. Task Adaptation

To model variability in task, we model a functional task using a machine learning algorithm that learns and generates arbitrarily complex multi-joint rhythmic movement patterns using nonlinear dynamical systems [44]. This approach uses a canonical limit cycle oscillator with well-defined stability properties and modifies the attractor landscape of the canonical system using statistical learning methods to embed arbitrary smooth target patterns without loosing the stability properties. This learned pattern generator is an autonomous dynamical system which can robustly deal with external perturbations that disrupt the time dependent flow of the original motion pattern. Another important aspect of this approach is that it will allow for on-line modifications of the target trajectory. The variability in the learned task can be then introduced by changing the frequency and amplitude parameters of the non-linear dynamical system based on performance. This approach allows us to model any periodic task in the form of a time based trajectory (e.g. position or torque trajectory).

1) Modeling Task: We use a nonlinear oscillator (1) to create a rhythmic phase variable (ϕ) that governs the desired output trajectory (2) using a learned nonlinear function (3).

$$\begin{aligned}\dot{x}_1 &= -\frac{\mu}{r_0}(r - r_0)x_1 - k^2 x_2 \\ \dot{x}_2 &= \frac{x_1}{(1 + \kappa_{x_2}(\mathbf{y} - \mathbf{y}_d)^T(\mathbf{y} - \mathbf{y}_d))}\end{aligned} \tag{1}$$

$$\dot{\mathbf{y}} = \mathbf{f} + \beta(\mathbf{y}_m - \mathbf{y}_d) + \kappa_y(\mathbf{y} - \mathbf{y}_d) \tag{2}$$

$$\mathbf{f} = \mathbf{\Psi}(\phi)\mathbf{w}\sqrt{r_0} \tag{3}$$

where x_1 and x_2 are the states of the oscillator, parameter k corresponds to the frequency of the oscillator, r_0 corresponds to the desired total energy and determines the amplitude of the oscillation, μ determines the convergence rate to the limit cycle and β is a positive constant. $\mathbf{y}_m$ is a parameter which determines the mean around which $\mathbf{y}$ oscillates. $\mathbf{y}$ and $\mathbf{y}_d$ are the measured and the desired output, respectively. κ_{x_2} and κ_y are the output feedback gains for x_2 and $\dot{\mathbf{y}}$, respectively. $\mathbf{\Psi}$ is the matrix with Gaussian kernel function given in (4).

$$\psi_i = e^{-\frac{(\phi - c_i)^2}{\sigma_i^2}} \tag{4}$$

$$\phi = \tan^{-1}\left(\frac{x_1}{kx_2}\right) \tag{5}$$

where c_i and σ_i represent the mean and variance of the Gaussian, respectively. The non-linear oscillator has a stable limit cycle characterized by the closed trajectories as in (6)

$$\frac{x_1^2}{2} + \frac{k^2 x_2^2}{2} = r_0 \tag{6}$$

and energy at any state (x_1, x_2) as

$$r(x_1, x_2) = \frac{x_1^2}{2} + \frac{k^2 x_2^2}{2} \tag{7}$$

To learn the nonlinear function $\mathbf{f}$ from a given desired trajectory ($\mathbf{y}_d$), we solve a nonlinear function approximation problem to find the parameters $\mathbf{w}$ in (3). Given the sampled trajectory data ($\mathbf{y}_d$), we obtain the target function using (8)

$$\mathbf{f}_{target} = \dot{\mathbf{y}}_d - \beta(\mathbf{y}_m - \mathbf{y}_d) \tag{8}$$

We use an incremental radial basis function network to learn the target function, which has been shown to be more robust and generate compact networks [45]. Such a learning algorithm can allocate resources as needed while dealing with the bias-variance dilemma in a systematic way.

2) Incorporating Variability in Learned Task: We model the amplitude and frequency of the learned task as a function of performance on the task as in (9). We consider the error over N time steps to assess performance instead of instantaneous performance to take into account the averaged performance, which gives a more accurate estimate of the skill level of the subject.

$$\begin{aligned} \text{Amplitude: } r_0 &= e^{-\kappa_r \frac{1}{N}\sum_{i=1}^{N}\left(\mathbf{y}_i-\mathbf{y}_{i,d}\right)^T\left(\mathbf{y}_i-\mathbf{y}_{i,d}\right)} \\ \text{Frequency: } k &= k_0 e^{-\kappa_k \frac{1}{N}\sum_{i=1}^{N}\left(\mathbf{y}_i-\mathbf{y}_{i,d}\right)^T\left(\mathbf{y}_i-\mathbf{y}_{i,d}\right)} \end{aligned} \tag{9}$$

where κ_r and κ_k are the parameters associated with amplitude and frequency, respectively. k_0 is the maximum desired frequency and n refers to the number of output trajectories being tracked. $\mathbf{y}_i$ and $\mathbf{y}_{i,d}$ represent the actual and the desired joint torque vector for i^{th}. According to this model as the error increases the relative amplitude of the motion reduces from one towards zero and the frequency of the motion reduces from k_0 towards zero.

B. Assistance Adaptation

Incorporating both performance-based error augmentation or haptic guidance training requires a controller that could seamlessly transition from haptic guidance regimen to an error-augmentation one. We incorporate performance-based error augmentation or haptic guidance in the control algorithm using adaptive impedance control as given by (10).

$$\begin{aligned} \theta_{m,j,ff} &= k_{j,ff}\frac{1}{r_m}\left(\frac{y_{j,d}}{2k_j r_j}\right) \\ k_{j,ff} &= \text{mtanh}\left(\frac{1}{N}\sum_{i=1}^{N}\left(y_{j,i}-y_{j,i,d}\right)^2\right) \end{aligned} \tag{10}$$

where $\theta_{m,j,ff}$ represents the feed-forward motor position for the j^{th} exoskeleton joint, which is calculated using the desired joint torque ($y_{j,d}$), exoskeleton SEA joint stiffness (k_j) and joint and motor pulley radii (r_j and r_m). $k_{j,ff}$ is the gain for the j^{th} joint that determines the amount of assistance provided by the exoskeleton based on the torque tracking performance of the subject on the task. $y_{j,i}$ and $y_{j,i,d}$ represent the actual and the desired torque of the j^{th} joint of the exoskeleton for i^{th} sample, respectively. In this type of control both gain and trajectory adaptations take place. The gain is adapted such that the controller gain becomes negative (error augmentation training) as the error becomes very low and increases (haptic guidance) as the error becomes large. We use modified hyperbolic tangent function (mtanh(.)) for gain adaptation to realize such an adaptation.

C. Visual Feedback Adaptation

We incorporate performance-based visual feedback by changing the transparency of the visual feedback based on the performance on the task as in (11).

$$t_{j,r} = k_{j,t}\left(1 - e^{-\kappa_{j,t}\sum_{i=1}^{N}\left(y_{j,i}-y_{j,i,d}\right)^2}\right) \tag{11}$$

where $t_{j,r}$, $k_{j,t}$ and $\kappa_{j,t}$ represent the degree of transparency, transparency gain and the parameter governing the rate at which the transparency changes with change in torque tracking error, respectively, corresponding to the j^{th} joint. The visual feedback becomes less transparent, i.e., less visible, as the performance over the task improves, making the task more challenging for the subject.

VI. Experimentation

We carry out experimentation to evaluate first the functionality of the framework and then use the framework to test a hypothesis on motor learning of healthy subjects using our previously developed hand exoskeleton [46].

A. Task Modeling

For the task to be learnable for healthy subjects, we chose the simultaneous tracking of torque trajectories at the two joints of index finger exoskeleton as the task for our experiments. We limit the task to two joints as a visual feedback is associated with the task and simultaneously observing more than two trajectories is very challenging for the subject. In order to develop a torque-based task that is closer to the natural finger motion, we first run the index finger exoskeleton in zero-torque mode and perform a finger flexion-extension task with a healthy subject. During this motion, we collect the exoskeleton joint angle trajectories and learn a model using the approach presented in Section V-A.1. In order to generate the torque trajectory associated with this task, we then run the device in impedance control mode to track the learned trajectories. The recorded exoskeleton joint torque trajectories are then again learned using the learning-from-demonstration approach. Finally, the torque task is generated using the learned dynamic model.

B. Task, Assistance and Visual Feedback Adaptation

The three adaptations presented in Section V are then introduced in the modeled torque tracking task. We tested the functioning of the framework by letting a subject perform the torque tracking task and observing the variation in task amplitude and frequency, joint impedance and transparency of visual feedback.

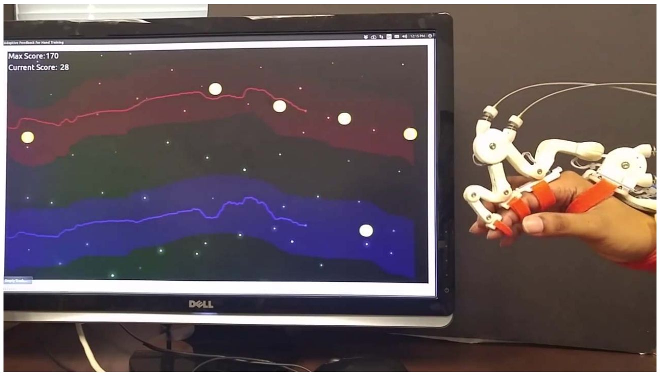


Fig. 2. The index finger exoskeleton module and the graphical user interface presented to the subject for the motor learning study.

C. Hypothesis Testing

We carry out a pilot human subjects study with the goal of understanding if the subjects could learn the task when trained in the presence of three types of adaptations as incorporated in the framework. Seven healthy subjects (six male and one female, ages 19-66) with no history of any neuromuscular injury, voluntarily participated in the experiments, after they provided their informed consent. The study was approved by The University of Texas at Austin institutional review board.

1) Hypothesis: Training using simultaneous adaptation of task, assistance and feedback based on performance positively affects motor learning of healthy human subjects on a torque-based task as compared to no training.

2) Training Task: The torque tracking task was presented to the subject in the form of an engaging game (Fig. 2). The graphical user interface for the game consists of two torque tunnels corresponding to the two joints of the index finger. The subjects are asked to build appropriate level of torque at the two exoskeleton joints such that they could travel in the two tunnels as far as possible without hitting the boundaries of either tunnel. The current torque level is shown to the subject in the form of a visual feedback whose transparency is governed based on the performance on the task. Rewards in the form of coins are presented at the center of the tunnel, which corresponds to the desired torque trajectory and the subjects are encouraged to collect as many coins as possible while navigating the tunnels to score higher in the game. The game becomes progressively more difficult as the width of each tunnel reduces linearly as subjects travel farther in the tunnels. The total score consists of the sum of how long a subject could survive in the game and how many coins the subject collects on his or her way. A higher score in the game reflects a subject's capability to dynamically generate desired level of torque at the two finger joints under uncertain visual feedback. Both the current and maximum score is also shown to encourage active participation of the subjects in the task.

3) Evaluation Task: To assess the skill level of the subject, an evaluation task was presented to the subjects in the form of a challenging game. For the evaluation task, the task frequency and amplitude (13), resistive feed-forward assistance gain (14) and visual feedback transparency (15) were varied with three different random variables ($\chi_k, k = \{1,2,3\}$) uniformly distributed between 0 and 1 (12). This ensures that each subject is presented with a task that has a similar level of challenge.

$$\chi_k \sim U([0,1]), k = \{1,2,3\} \tag{12}$$

$$\begin{aligned} \text{Amplitude: } r_0 &= e^{-\kappa_r \chi_1} \\ \text{Frequency: } k &= k_0 e^{-\kappa_k \chi_1} \end{aligned} \tag{13}$$

$$k_{j,ff} = \mathrm{mtanh}\,(\chi_2) \tag{14}$$

$$\text{Transparency: } t_r = k_{j,t}\left(1 - e^{-\kappa_t \chi_3}\right) \tag{15}$$

where $U([a,b])$ represents a uniform distribution between a and b.

4) Protocol: The study consisted of five training and three evaluation sessions. In each training session the subjects played the game with the training task for at least 15 minutes. Each training session was conducted on a separate day to ensure that subjects could learn and retain the task from session to session. For evaluation, each subject was presented with 10 trials of the evaluation task to assess the level of skill of the subject. Each subject was evaluated before, in the middle of and after training to assess any improvement in performance on the task. In the first session, each subject was tested on the evaluation task to assess the pre-training performance. The subjects were then trained for three sessions using the training task and the performance is assessed again using the evaluation task at the end of third session. Finally, the subjects were trained for two sessions and their performance was again assessed at the end of fifth training session. The post-, mid- and pre-training performance were then compared to understand if statistically significant improvement in performance is observed. During experiments the subjects were not informed whether they are being trained or evaluated.

VII. Results

A. Task Modeling

Results show that the exoskeleton joint angle task trajectories are reproduced by the learned dynamic model for both the joints (Fig. 3(c)). The states and phase of the nonlinear oscillator which governs the generation of the joint angle trajectory show periodic motion (Figs. 3(a) and (b)). Also, the exoskeleton joint torques generated using the learned dynamic model reproduce the torque trajectories measured from the device as obtained using impedance control (Fig. 3(d)).

B. Task, Assistance and Visual Feedback Adaptation

Results show that the three types of performance-based adaptations are captured by the framework and are reflected while performing the task. The task amplitude reduces as the torque root mean square (RMS) error increases and vice versa (Fig. 4(b)). The feed-forward assistance gain varies as per (10) as the torque RMS error changes (Fig. 4(c)). The transparency of the visual feedback decreases, i.e., the

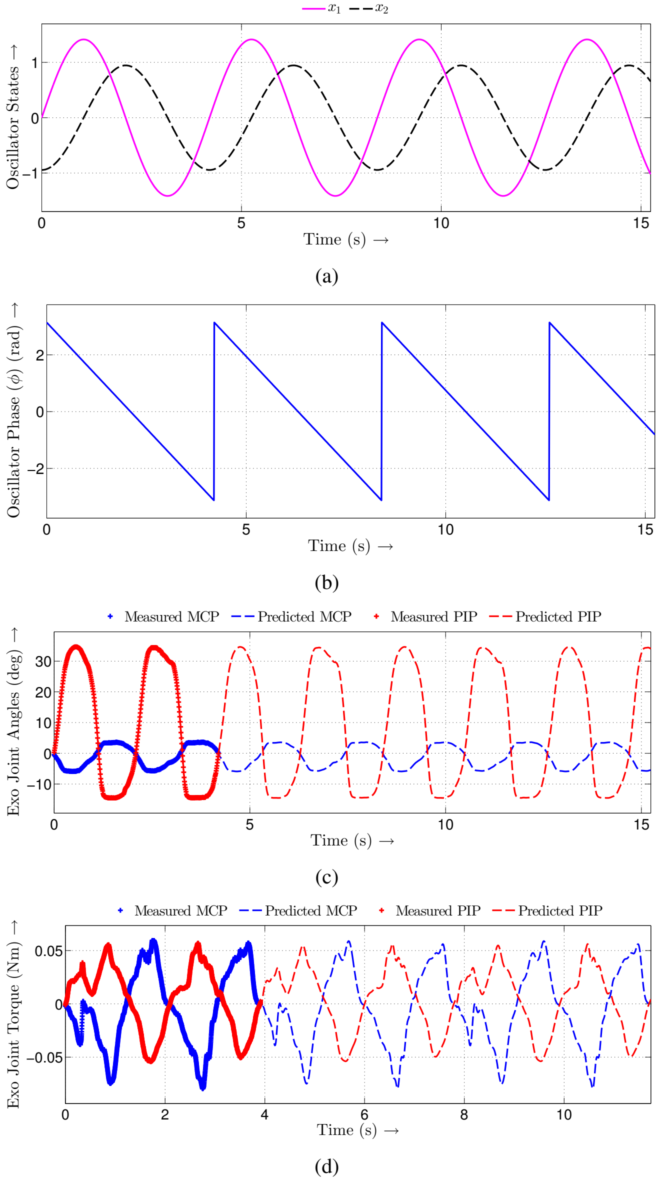


Fig. 3. The finger flexion-extension task as modeled using the learning-from-demonstration approach. (a) The states and (b) phase angle of the nonlinear oscillator corresponding to the exoskeleton joint angle trajectories, (c) measured and generated exoskeleton joint angle trajectories for the two exoskeleton joints and (d) measured and generated exoskeleton joint torques.

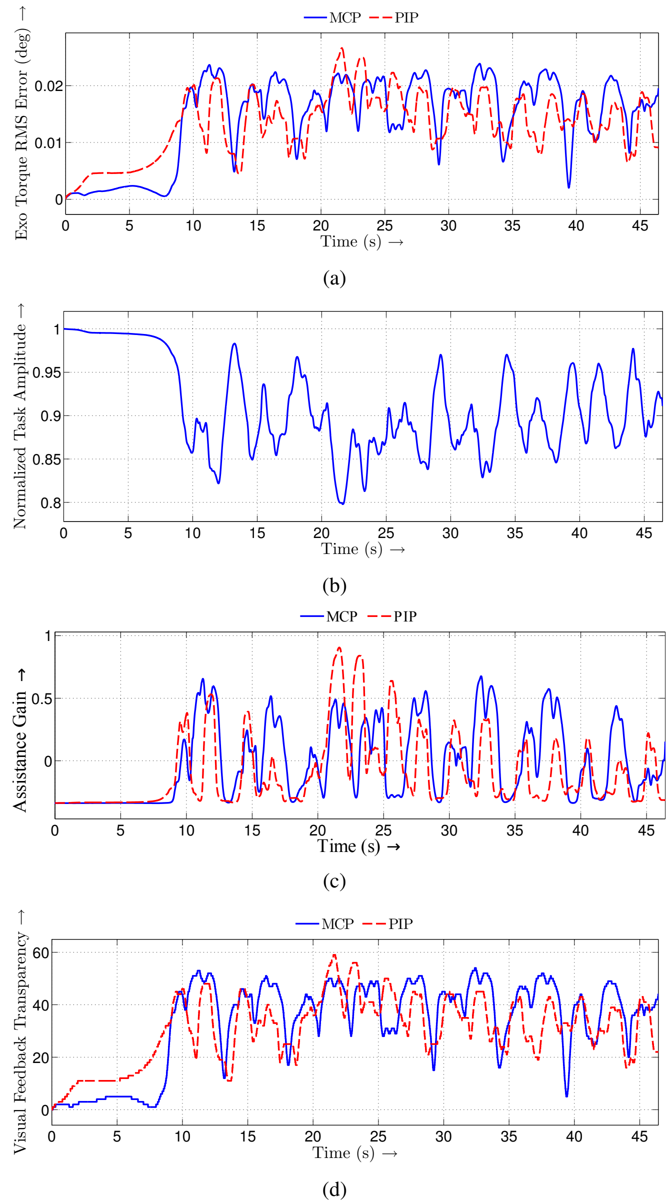


Fig. 4. The three types of adaptations as implemented in the framework for the torque tracking task. (a) Exoskeleton joint torque RMS error trajectories, (b) normalized task amplitude and frequency trajectories, (c) exoskeleton feed-forward assistance gain trajectories and (d) visual feedback transparency trajectories for the two exoskeleton joints.

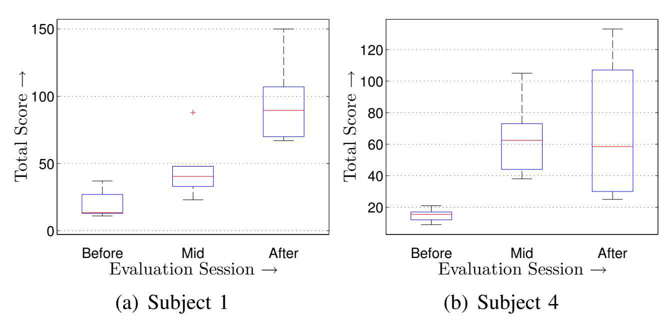
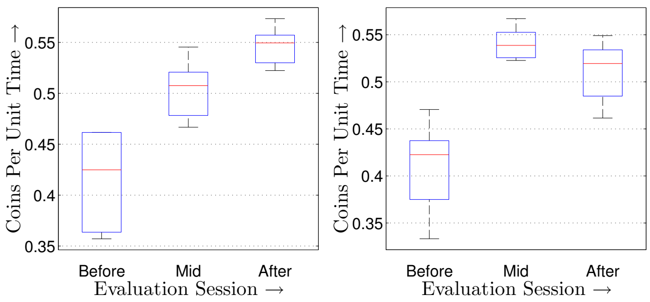


Fig. 5. The box plot of the total score for subjects 1 and 4 in the evaluation sessions conducted before, in the middle of and after training. The central mark represents the median, the edges of the box are the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles, the whiskers extend to the most extreme data points not considered outliers and the outliers are plotted individually.

trajectory becomes less visible as the torque tracking error reduces making the task more challenging. Thus, the three adaptations ensure that the task is consistently challenging for the subject even when the skill level of the subject changes.

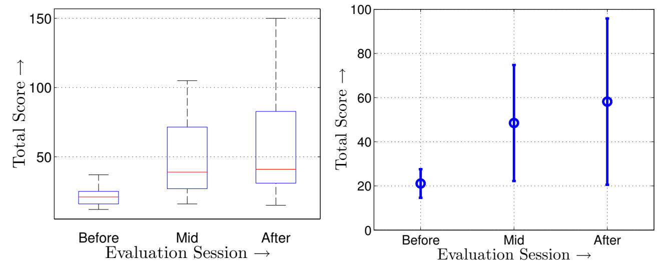
C. Hypothesis Testing

1) Total Score: Results from the human subjects study showed that the performance of 6 out of 7 subjects improve in the evaluation session when trained using the presented framework (Fig. 5). A few different learning trends were also observed. Some subjects showed a steady improvement in performance from pre- to post-training evaluation. While some form of saturation in performance was visible in



(a) Subject 1 (b) Subject 4

Fig. 6. The box plot of the coins collected per unit time for subjects 1 and 4 in evaluation sessions conducted before, in the middle of and after training.



(a) (b)

Fig. 7. Combined total score for all subjects in evaluation sessions conducted before, in the middle of and after training. (a) Box plot of the total score and (b) Error bar plot of the total score. The center in the error bar represents mean and whiskers represent two standard deviation units in length.

the performance of others. Only one subject showed an improvement from pre- to mid-training session and a decline in performance from mid- to post-training evaluation. Thus, training using our framework positively affects the motor learning of the subjects.

2) Tracking Performance per unit Time: Another important way to assess the improvement in the skill of the subjects is to determine how accurately a subject played as they could survive for a longer duration from session to session. We evaluated tracking performance per unit time metric to assess this improvement in the skill. Since the coins are located on the desired trajectory, the number of coins collected by a subject indicates the tracking performance of the subject. Thus, coins collected per unit time is a measure of the skill level of the subject. Results showed that tracking performance per unit time improves for 6 out of 7 subjects with training (Fig. 6). Thus, subjects not only could survive longer as they are trained using the presented framework they also get better at playing the game.

3) Statistical Analysis: Both the median and mean scores in the evaluation sessions improved with training considering scores of all subjects (Fig. 7). However, statistics showed that the variance of score also increase with training. Thus, as subjects get better at playing the game they also become less consistent at achieving the same score. A paired-samples t-test was conducted to compare the evaluation scores of all subjects before and after training. There was a significant difference in scores before (M=21.1, SD=6.5) and after training (M=58.2, SD=37.7); $t(34)=-6.05$, $p<0.0001$. These results support the hypothesis that simultaneous adaptation of task, assistance and visual feedback positively affects motor learning on a torque-based task.

VIII. CONCLUSION

We presented a framework for robot-assisted motor (re)-learning that incorporates subject-specific training. The framework allows for simultaneous adaptation of task, assistance and feedback based on the performance of a subject on a task to keep the task sufficiently challenging for the subject. As a part of the framework development, we presented a learning-from-demonstration approach to model a coordinated task to modulate the challenge level of the task in an online manner. We also presented a torque-based task that trains subject to dynamically regulate joint torques similar to that needed for dexterous manipulation. Finally, we conducted a pilot study with human subjects and the results suggested that a training paradigm that simultaneously adapts the task, assistance and feedback positively affects motor learning of healthy human subjects on a torque-based task.

In the future, we plan to test several different hypothesis using the proposed framework to understand the role of each component and how rate of different types of adaptations influence motor learning. We also plan to focus on testing hypotheses to examine the efficacy of this multi-modal challenge modulation for different tasks. Furthermore, we plan to design training paradigms for stroke subjects using the developed framework that are based on simpler tasks.

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